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PREDICTION OF TRAFFIC SIGN VANDALISM THAT OBSTRUCTS CRITICAL MESSAGES TO DRIVERS

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Abstract. A critical deficiency in any one or a combination of three transportation system characteristics: the driver, roadway, or vehicle can contribute to an elevated crash risk for the motoring public. Traffic signs often convey critical information to drivers. However, traffic signs are only effective when clearly visible and legible. Traffic sign vandalism that is exclusively the results of humans causes both sign legibility and visibility to deteriorate. Transportation agencies spend a significant amount of money to repair or replace vandalized signs. This study was conducted to identify which traffic signs are more vulnerable to vandalism. To do this, a mobile-based vehicle collected data of over 97000 traffic signs managed by the Utah Department of Transportation (UDoT), US. The vandalized signs were identified by a trained operator through inspection of daytime digital images taken of each individual sign. Location data obtained from online sources combined with the traffic sign data were imported into ArcGIS to acquire localized conditions for each individual sign. According to the chi-square test results, the association between vandalism and traffic sign attributes and localized conditions, including background color, size, mount height, exposure, land cover, and road type was evident. After employing the random forests model, the most important factors in making signs vulnerable to vandalism were identified.

Keywords: transportation infrastructure; traffic sign vandalism; mobile-based data collection; mobile LiDAR; digital imaging; geographic information system; random forests.

Introduction

A variety of factors associated with drivers, vehicles and the roadway contribute to the likelihood of crashes. Transportation agencies continually make efforts to design safety improvements that will reduce such outcomes, with particular concern for fatal and serious injury crashes (Baratian-Ghorghi *et al.* 2015). Of all types of transportation infrastructure, traffic signs are the most frequent visual aids. Their task is providing safer traffic environments through regulating, warning, or guiding road users. The placement of key traffic signs, such as stop signs, yield signs, and speed limits, increases traffic safety (Borowsky *et al.* 2008). Previous studies showed that drivers behavior can be dramatically influenced after the placement of yield to pedestrian at crosswalks signs (Ellis *et al.* 2015), work-zone warning signs and school zone signs (Strawderman *et al.* 2015).

In order for road users to comprehend traffic signs, high legibility and visibility are critical (Ye *et al.* 2014). The overall legibility of a sign declines when the face of a sign is damaged (Boggs *et al.* 2013). Depending on the form of damage, the effects on legibility vary considerably. A number of sign damage forms are exclusively the result of humans. The overall day and night-time legibility of the sign can be affected by vandalism (Evans *et al.* 2012). In addition, tremendous amounts of money are spent to repair or replace vandalized signs (Harris 1992). Types of human vandalism include shooting paintballs, shooting bullets, throwing beer bottles, putting stickers on signs, and painting graffiti on signs. Although traffic sign vandalism has become a serious problem for traffic agencies (Chadda, Carter 1983) few studies are conducted that focus on this issue. Previous studies have estimated the costs of sign vandalism (Smith, Simodynes 2000), developed methods for sign vandalism detection (Mueller 1995), and examined the effects of releasing information in the media to reduce sign vandalism (Ellison 1996). A study examined the association between

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traffic sign vandalism and demographics of local population (Khalilikhah *et al.* 2016).

The countermeasures against vandalism have been discussed with regard to the form of sign vandalism, including utilizing more resistant materials to construct signs, mounting signs higher, applying penalty notices to signs, and using public information campaigns (Picha 1997; Perkins, Barton 1997). However, it is necessary to identify traffic signs that are more vulnerable to vandalism before installing them. This research was conducted to accomplish this goal. To do so, mobile-based data of 97000 traffic signs managed by the Utah Department of Transportation (UDoT) was collected. Mobile-based data provided sign attributes data, including background color, sign size, and mount height. The vandalized signs were identified by an operator through inspection of daytime digital images taken of each individual sign. Location data obtained from online sources combined with the traffic sign data was imported into ArcGIS to acquire localized conditions for each individual sign. The random forests model was employed to determine what traffic signs were more likely to be damaged by vandals.

1. Traffic Sign Data Description

1.1. Background

Traffic signs convey critical information to drivers. The process of conveying messages involves an interaction between signs and drivers. Some studies focused on the road user characteristics to investigate the understandability and comprehensibility of traffic signs. Other studies examined sign visibility and legibility with regard to sign attributes, location, and climate conditions (Bullough *et al.* 2010; Khalilikhah, Heaslip 2016a). Recently, a study examined the effectiveness of roadside signs in comparison to the in-vehicle auditory traffic information (Ma *et al.* 2016). Khalilikhah *et al.* (2015a), Khalilikhah, Heaslip (2016b) examined the effects of emissions of sign visibility and legibility. Multiple studies were performed focusing on the assessment and management of traffic signs (Ré, Carlson 2012; Balali, Golparvar-Fard 2015). Another study discussed the design of traffic signs (Stanić, Vujin 2005). However, little research exists regarding traffic sign vandalism. The objective of this research is to determine what types of traffic signs are more vulnerable to traffic sign vandalism.

1.2. Data Collection Method

In 2012, a mobile-based data collection effort was conducted in Utah to measure all traffic signs under the jurisdiction of the Utah Department of Transportation (UDoT). This comprehensive approach was carried out by an instrumented vehicle driven at freeway speeds that collected asset data on the roadway in real time (Fig. 1). The sensors on the vehicle included: a LiDAR sensor, a laser road imaging system, a laser rut measurement system, a laser crack measurement system, a road surface profiler, and a position orientation system. In conclusion, data of over 97000 traffic signs was collected on roadways along over 6000 miles of state routes and interstates. In addition, imaging technologies were integrated to automatically collect high-resolution detailed images from the assets. After conducting post-processing analysis by survey, the desired sign attributes data were derived, including location (latitude and longitude), size, orientation, and mount height. An operator also examined the captured daytime digital images, and noted damaged or deteriorated traffic signs throughout the entire data set (Khalilikhah *et al.* 2015b).

1.3. Sign Damage Categories

Data analysis conducted by the authors showed that almost 7% of all measured signs were damaged. Traffic signs exhibited various forms of damage, including being bent, delaminated, dented, dirty, faded, fallen, defaced by graffiti or paint, obstructed, rusty, and covered by stickers. Either humans or nature could have caused

a)

b)

Fig. 1. Mobile-based data collection: a – equipped vehicle (source: *http://mandli.com*); b – taking image of traffic signs (source: *http://168.178.125.102/roadview.asp?Route=0080P&Mile=61.6*)

Fig. 2. Samples of traffic sign vandalism
(source: photos taken by our research team)

these forms of damage. Ultimately, we categorized damage forms into two groups: vandalism or naturally occurrences. To do so, we used a sample data set collected by our research team in the field, including photos taken of about 1700 traffic signs. Vandalism included any deliberate damage to the sign face, including stickers, painting, dents, gunshots, and or graffiti, as shown in Fig. 2. Natural damage forms consisted of deterioration formed over timte, damage forms were the result of weather or other natural factors, or damage unintentionally caused by humans. The locations of the vandalized signs are shown in Fig. 3.

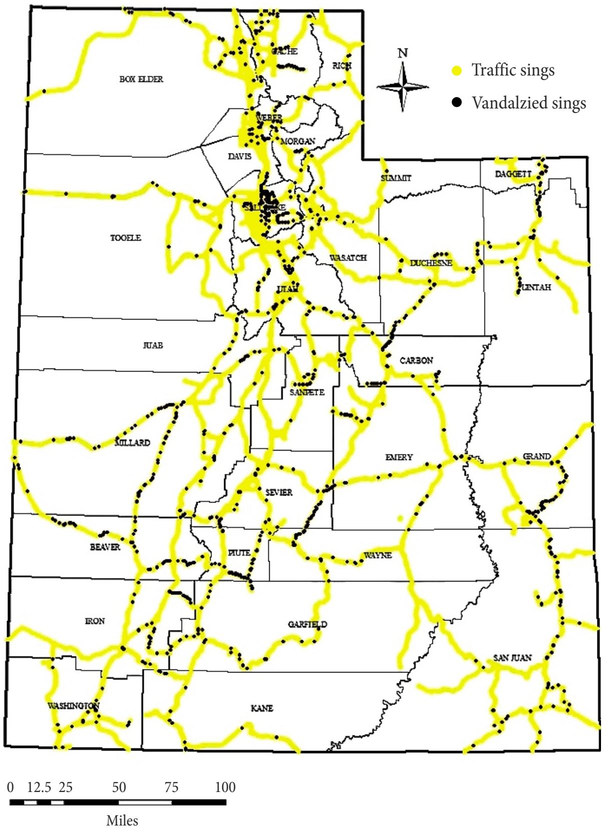

Fig. 3. Locations of vandalized traffic signs in Utah

2. Data Analysis

2.1. Sign Vandalism by Manual on Uniform Traffic Control Devices (MUTCD) Type

Table 1 provides a summary of the vandalized traffic signs based on the Manual on Uniform Traffic Control Devices (MUTCD) types. The Manual of Traffic Signs (Moeur 2014) was used to list traffic signs based on their type and sub-type. Respectively, regulatory, warning, marker, and guide signs made up almost 18, 20, 20, and 23% of over 97000 measured traffic signs. As a whole, warning signs, by far, exhibited the highest vandalism rate. Of vandalized signs, 53% were warning signs. With regard to the percentage of sign vandalism, turn and curve warning signs showed the highest rates, comprising approximately 30% of vandalized signs. 8% of the vandalized signs were advance warning/crossing, 7% were speed regulation signs and 9% were object markers. Interestingly, nearly 11% of vandalized signs were signs that deal with speed limits (speed regulation and advisory speed signs).

Based on the sign legend type, vandalized signs were categorized into four groups: text, symbol, arrow, and text/symbol/arrow. To be categorized as a text sign, these signs need words or digits to accomplish their tasks. Examples of text signs included speed limit signs (R2–1), mileposts (D10–1), and supplemental distance signs (W16–2 and 3). Symbol signs consisted of those that use symbols, rather than words or digits to interact with road users. Examples included school signs (S1–1), no pedestrian signs (R9–3a), and cattle or deer crossing signs (W11–3 and 4). The arrow category included any traffic signs employing arrows to regulate, warn, or guide drivers. For example, straight optional lane signs (R3–6L or R), reverse turn signs (W1–3L or R), and arrow auxiliary signs (M6–1L or R). The data also identified a final group of signs that included a combination of text, symbols, and arrows. These signs were included in the text/symbol/arrow grouping, such as do not enter signs (R5–1), stop ahead signs (W3–1), and destination with distance signs (D1–1, 2 and 3). Ultimately, it was found that arrow signs had the highest rate of vandalism, followed by text signs (Fig. 4).

Table 1. Summary of vandalized signs by MUTCD type

Traffic sign		MUTCD code	# of signs				%
Type	Name		Text	Symbol	Arrow	T/S/A	
Regulatory Signs	Stop and yield	R1 series	32	–	–	–	2.1
	Speed regulation	R2 series	106	–	–	–	7.1
	Turn and land use	R3 series	5	–	5	5	1.0
	Movement regulation	R4 series	1	–	6	4	0.7
	Selective exclusion	R5 series	1	1	–	1	0.2
	One way	R6 series	–	–	–	3	0.2
	Pedestrian and bicycle	R9 series	–	1	–	–	0.1
	Traffic signal	R10 series	2	–	–	2	0.3
	Road closed	R11 series	2	–	–	–	0.1
Warning signs	Turn and curve	W1 series	–	–	456	–	30.4
	Intersection	W2 series	–	–	22	–	1.5
	Advance traffic control	W3 series	1	–	–	15	1.1
	Merge and lane transition	W4 series	–	–	32	–	2.1
	Divided highway	W6 series	–	–	6	–	0.4
	Hill	W7 series	5	1	–	6	0.8
	Pavement condition	W8 series	15	2	–	–	1.1
	Railroad and light rail	W10 series	–	–	–	2	0.1
	Advance warning / Crossing	W11 series	–	123	–	–	8.2
	Low Clearance	W12 series	–	–	3	1	0.3
	Advisory Speed	W13 series	54	–	–	–	3.6
	Dead end / No outlet / No passing	W14 series	1	–	–	–	0.1
	Supplemental plaques	W16 series	30	–	19	–	3.3
Marker signs	Route markers	M1 series	52	–	–	–	3.5
	Junction signs	M2 series	5	–	–	–	0.3
	Cardinal direction auxiliaries	M3 series	5	–	–	–	0.3
	Advance turn auxiliaries	M5 series	–	–	2	–	0.1
	Directional arrow auxiliaries	M6 series	–	–	37	–	2.5
	Object markers	OM series	–	–	138	–	9.2
Guide & Information signs	Destination	D1 series	–	–	–	36	2.4
	Distance	D2 series	14	–	–	–	0.9
	Recreational	D7 series	9	–	–	15	1.6
	General services	D9 series	–	4	–	–	0.3
	Mileposts	D10 series	70	–	–	–	4.7
	Crossover / Freeway entrance	D13 series	2	–	–	–	0.1
	Interchange advance	E1 series	2	–	–	–	0.1
	Exit gore	E5 series	–	–	–	2	0.1
	Destination	E6 series	–	–	–	10	0.7
	Destination	E10 series	–	–	–	4	0.3
	General information	I series	11	–	–	–	0.7
School signs		S1, S3 and S5 series	11	6	–	–	1.1
Other signs			59	20	1	14	6.3

The question of interest was if traffic sign vandalism corresponds to specific types of signs. In other words, the authors conducted this research to figure out what attributes of traffic signs make them more likely to get vandalized. Questions to be answered include:

- do vandals select traffic signs based on sign color, size, or mount height?
- do localized conditions, such as exposure (urban or rural) and road type (major or ramp) make them more vulnerable to vandalism?

The next sections find answers for these questions.

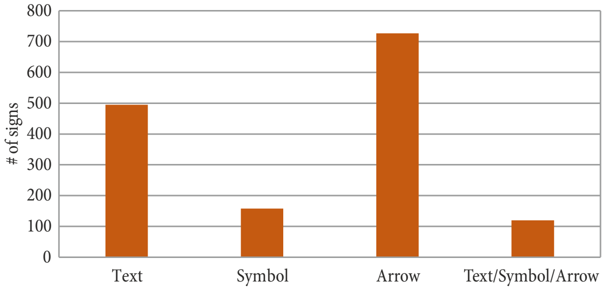

Fig. 4. Number of vandalized traffic signs by legend type

2.2. Signs Attributes

The association between traffic signs attributes and localized conditions and vandalism rates was tested using chi-square test. A summary of the association between the sign attributes and sign vandalism is provided in the following.

2.2.1. Sign Background Color

Green, red, white, yellow, black, blue, orange, and brown were the observed background colors of surveyed signs. Respectively, 22, 23 and 29% of the surveyed signs were green, white, and yellow, while the other colors collectively made up only 26% of the total. Table 2 depicts a summary of the sign vandalism rates based on the sign background color. Warning signs are typically yellow (DoT 2012). Thus, yellow signs tend to have a relatively higher vandalism rate. According to the results of the chi-square test, there is strong evidence of an association between sign vandalism rate and sign background color.

Table 2. Traffic sign vandalism by color

Color	# of signs	Vandalism		Vandalized [%]
		yes	no	
Green	21112	145	20967	0.69
Red	1937	33	1904	1.70
White	28610	240	28370	0.84
Yellow	22844	843	22001	3.69
Others	22811	239	22572	1.05
Chi-square test statistic = 926.65				
p-value <0.0001				

2.2.2. Sign Length and Width

To ensure adequate message comprehensibility, the appropriate size of each sign should be determined based on the task of sign and the prevailing traffic speed on the road (VDoT 2011). Tables 3 and 4 display the corresponding sign vandalism ratings for each category of length and width. Generally speaking, the percentage of vandalized signs changes little among different categories of length or width, with the exception of signs with width from 24 to 36 inches and length of between 30 and 40 inches, which is mostly the size of warning signs. The chi-square value is statistically significant. Thus, there is evidence of an association between sign size and vandalism rate.

Table 3. Traffic sign vandalism by width

Sign width [in]	# of signs	Vandalism		Vandalized [%]
		yes	no	
<18	19350	232	19118	1.20
18–24	33720	422	33298	1.25
24–36	22713	635	22078	2.80
36–54	8421	113	8308	1.34
>54	13110	98	13012	0.75
Chi-square test statistic = 325.75				
p-value <0.0001				

Table 4. Traffic sign vandalism by length

Sign length [in]	# of signs	Vandalism		Vandalized [%]
		yes	no	
<20	24112	170	23942	0.71
20–30	22051	216	21835	0.98
30–40	37309	970	36339	2.60
40–60	7903	105	7798	1.33
>60	5939	39	5900	0.66
Chi-square test statistic = 465.44				
p-value <0.0001				

2.2.3. Sign Mount Height

According to the summary of sign vandalism by mount height (Table 5), signs placed higher were less likely to get vandalized. For signs placed 10 feet or more above the road, the vandalism rate was only 0.12%. Based on the results of the chi-square test, there is evidence of an association between sign vandalism rate and mount height.

Table 5. Traffic sign vandalism by mount height

Sign height above road [ft]	# of signs	Vandalism		Vandalized [%]
		yes	no	
<5	17160	272	16888	1.59
5–7	25707	632	25075	2.46
7–8	24020	427	23593	1.78
8–10	17718	154	17564	0.87
>10	12709	15	12694	0.12
Chi-square test statistic = 373.93				
p-value <0.0001				

2.2.4. Exposure

Our recent study reported that the sign vandalism rate for rural signs was greater than that of urban signs (Khalilikhah *et al.* 2016). We defined a variable called sign exposure (urban or rural) with respect to the area that the traffic sign was installed. To obtain sign exposure data, the Geographic Information Database of Utah's Automated Geographic Reference Center (Utah AGRC 2015) website was used. Then, rural and urban signs were identified using ArcGIS. A summary of the traffic signs vandalism by exposure is provided in Table 6. As seen in the table, the number of vandalized signs for rural exposure is indeed higher than for urban areas. The chi-square value was also statistically significant. Therefore, the association between sign exposure and number of vandalized signs was evident.

Table 6. Traffic sign vandalism by sign exposure

Exposure	# of signs	Vandalism		Vandalized [%]
		yes	no	
Urban	46611	410	46201	0.88
Rural	50703	1090	49613	2.15
Chi-square test statistic = 257.32				
p-value <0.0001				

To have a better sense of the environment surrounding these signs, we obtained 16-category land cover classification data from the National Land Cover Database 2011 – NLCD 2011 (MRLC 2011). NLCD 2011 applied the classifications consistently across the country at a spatial resolution of 1000 feet. It categorized land cover into the following groups:

- water (open water, perennial ice/snow);
- developed (open space, low intensity, medium intensity, high intensity);
- barren land (rock/sand/clay);
- forest (deciduous, evergreen, mixed);
- shrubland (dwarf scrub, shrub/scrub);
- herbaceous (grassland/herbaceous, sedge/herbaceous, lichens, moss);
- planted/cultivated (pasture/hay, cultivated crops);
- wetlands (woody wetlands, emergent herbaceous wetlands).

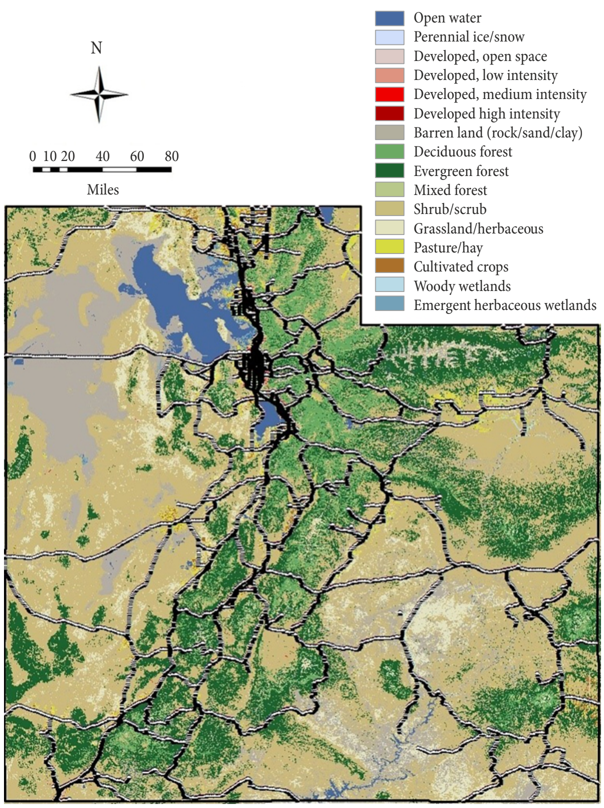

Fig. 5. Locations of traffic signs by land cover

To obtain the type of land cover for each individual sign, we created a raster data using ArcGIS (Fig. 5). Then, we extracted the land cover type surrounding the signs from the raster data. The results of this extraction are summarized in Table 7. As expected, the result of the chi-square test showed evidence of an association between the vandalism rate and type of land cover. Signs installed in areas labeled as forest had the greatest rate of vandalism. Importantly, almost 84% of the UDoT's signs were located in developed areas. By focusing upon developed areas, another trend could be observed: open space areas showed the highest rate of vandalism, and the lowest rate was exhibited by high-intensity areas.

Table 7. Traffic sign vandalism by land cover

Land cover	# of signs	Vandalism		Vandalized [%]
		yes	no	
Developed-open space	26956	564	26392	2.09
Developed-low intensity residential	24560	367	24193	1.49
Developed-medium intensity residential	19777	222	19555	1.12
Developed-high intensity residential	10843	107	10736	0.99
Bare rock/sand/clay	194	4	190	2.06
Forest	1658	46	1612	2.77
Shrub/scrub	9980	163	9817	1.63
Grasslands/herbaceous	553	8	545	1.45
Planted/cultivated	2183	13	2170	0.60
Wetlands	610	6	604	0.98
Chi-square test statistic = 130.77				
p-value <0.0001				

2.2.5. Road type

The (Utah AGRC 2015) data set was used to extract the type of road that traffic sign was installed on. To do so, ArcGIS was employed and ultimately traffic signs were categorized into two groups based on where they were placed. Category one was major road signs (87% of the measured signs), and category two was signs placed in ramps, rest areas, or turnarounds (13% of the measured signs) (Table 8). After running the chi-square test, the association between road type and sign vandalism rate was evident. The rate of sign vandalism for major road signs was higher than the other signs.

Table 8. Traffic sign vandalism by road type

Road type	# of signs	Vandalism		Vandalized [%]
		Yes	No	
Major	84423	1412	83011	1.67
Ramp (on/off)	12891	88	12803	0.68
Chi-square test statistic = 71.55				
p-value <0.0001				

2.3. Modeling

To identify traffic signs that were more likely to get vandalized, developing statistical models that could yield the desired results was needed. Through analysis of the collected data, it was observed that 1500 of over 97000 measured traffic signs were vandalized; this is approximately 1.5% of UDoT's signs. Thus, the response variable was extremely biased. In addition, the relationships among the explanatory variables was also thoroughly complex. The unknown, but likely, nonlinear relation between response and predictors was also expected. Besides, the data structure of multiple explanatory variables was enormously varied (nominal or ordinal, continuous or categorical, quantitative or qualitative). Traditional models, such as analysis of variance, log linear, and logistic regression were not able to address these issues. Instead, random forests model can simultaneously handle these challenges (Breiman, Cutler 2007; Moisen 2008). Random forests is a tree-based model that tends to have lower variance by taking repeated samples from a single data set and combining them together. Thus, random forests model includes a very large number of decision trees. Thus, the interpretation of random forests is awkward (James *et al.* 2013). To address this challenge, the variable importance measure is provided for random forests model. A greater importance value indicates that the predictor has a more significant role in the response.

Since predictors were measured with their own units, the authors also conducted a standardization of predictors to avoid the possible bias caused by a varied scale. To do this, a standard transformation was conducted, each variable subtracted its mean and divided by standard error. After standardization, the measurements of all predictors ranged from –1 to +1. Then, a random forests package was created in R Development Core Team (2014). The subset of variables considered in each splitting is suggested to be $m = \sqrt{p}$ (James *et al.* 2013). For this study, having 6 explanatory variables, including sign color, length, width, mount height, land cover, and road type, m equals three was considered. No particular rule or optimal number is suggested for the number of trees in the literature, although a larger number of trees did not lead to consistently better performance (Oshiro *et al.* 2012). For the current study, 1500 trees were developed, which is an appropriate number for such sample sizes. After obtaining the variable importance values from developing random forests model, importance values were normalized to make interpretation easier (Fig. 6). This was designed so that the most important predictor had an importance of 100 (Rebollo, Balakrishnan 2014).

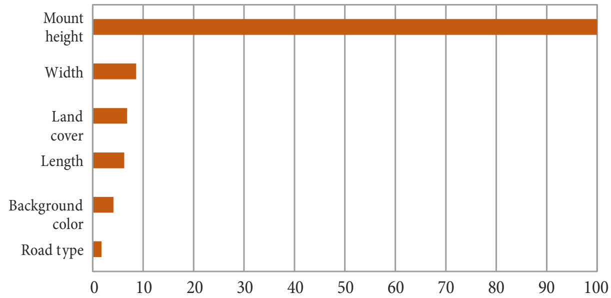

Fig. 6. Variable importance ranking for traffic sign vandalism

3. Discussion

As seen in Fig. 6, although all sign attributes were important to vandalism rates, the height of sign above the road was, by far, the most important variable. The importance of sign mount height reflects the fact that regardless of sign color, size and localized conditions, vandalism damage on the face of traffic signs is more frequent on ground mount signs. Despite this, the strong association between mount height and vandalism rate did not seem to be linear because the rate of vandalism for signs installed within 5 feet of the ground was less than those between 5 and 7 feet. While the average mount height for all measured signs was about 8 feet, the average height of vandalized signs was 6.5 feet above the road. The closeness of rankings of sign size, color, land cover, and road type may indicate an inner correlation or interaction between those predictors. To enable more in-depth analysis, the possible interaction between the most important variable, sign mount height, and other factors should be studied. Fig. 7 shows the Pearson correlation coefficient values (the covariance of the two variables divided by the product of their standard deviations). As seen in the figure, significant correlation between sign width and sign length is evident. The correlation between other variables was not significant.

As shown in Fig. 8, approximately, all of the vandalized signs located in rural areas or installed on ramps had a mount height less than 10 feet. Thus, mounting these signs higher can be a good countermeasure against sign vandalism. In addition, 53% of vandalized signs were warning signs. Turn and curve warning signs that comprised approximately 30% of vandalized signs, have an average mount height of 6.6 feet with 1.5 standard deviation.

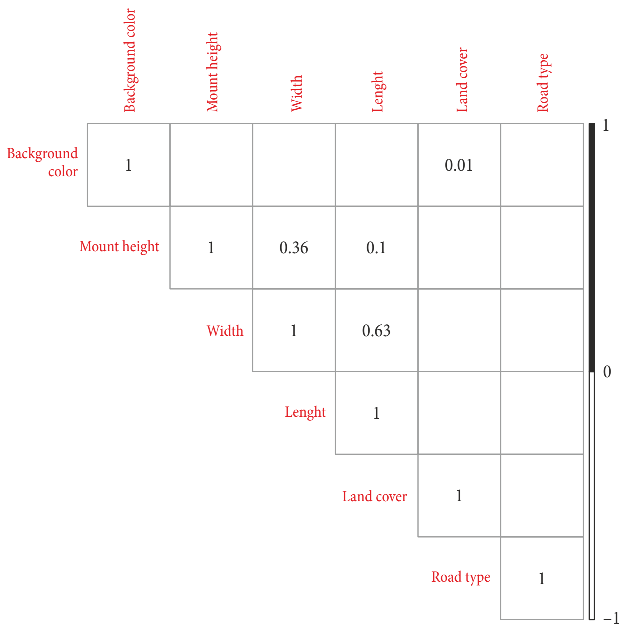

Fig. 7. Pearson correlation coefficient values

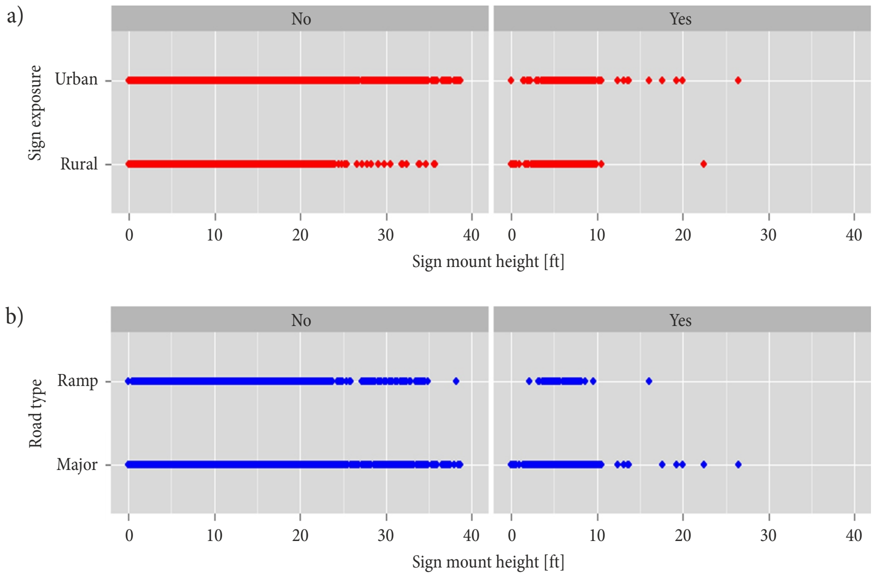

Fig. 8. Vandalized signs by mount height vs. (a) exposure and (b) road type

As a result, warning signs can also be mounted higher. However, most of warning signs are located on minor or local roads. Taking into consideration the signs located on ramps or in rural areas, increasing sign heights may dramatically affect sign visibility (especially during hours of darkness) since headlights will not reach higher sign heights. To address this issue, traffic signs can be equipped with internal or external lightening systems.

Conclusions

Traffic sign vandalism is a serious concern, since it causes a decline in the overall legibility and visibility of signs. Such events can lead to an increase in unsafe driving behaviors. It also results in increased costs to transportation agencies to replace, repair, or maintain the vandalized signs. This paper examined the association between vandalism rates and the traffic sign attributes and localized conditions, including sign background color, size (length and width), mount height, exposure, land cover, and road type. Initial analysis showed that warning signs had the highest vandalism rates. After further analysis, and according to the chi-square test results, the association between sign attributes and vandalism was evident. After employing random forests model, the ranking of the predictors on the rate of traffic sign vandalism was also extracted.

In case of considering countermeasures against sign vandalism, the findings of this study showed that priority given to turn and curve signs (W1 series), object markers (OM series), advance warning/crossing signs (W11 series), and speed regulation (R2 series) is warranted. Since the height of sign above the road was, by far, the most important factor, one suggestion is to install more vulnerable signs to vandalism higher above the road. To address the issue of being outside of lighted areas by headlights, traffic signs can be equipped with internal or external lightening systems. In this way, the evaluation of cost effectiveness of labor and material to do countermeasures against vandalism is the next step that should be taken.

The findings of this investigation may assist transportation agencies in determining traffic signs with a higher likelihood of sign vandalism based on sign attributes. Based on our findings, transportation agencies' policies could be changed to considering countermeasures against vandalism (before sign installation) and more frequent inspection (after sign installation) of the following traffic signs:

- signs with mount height between five and seven feet;
- signs placed in rural or low intensity urban areas, in particular, signs installed in areas with land cover labeled as forest;
- signs installed in roads with lower traffic, such as ramps.

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